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Graph-based structural change detection for rotating machinery monitoring

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ABSTRACT

Detection of structural changes is critically important in operational monitoring of a rotating machine. This paper presents a novel framework for this purpose, where a graph model for data modeling is adopted to represent/capture statistical dynamics in machine operations. Meanwhile we develop a numerical method for computing temporal anomalies in the constructed graphs. The martingale-test method is employed for the change detection when making decisions on possible structural changes, where excellent performance is demonstrated outperforming exciting results such as the autoregressive-integrated-moving average (ARIMA) model. Comprehensive experimental results indicate good potentials of the proposed algorithm in various engineering applications. This work is an extension of a recent result (Lu et al., 2017).

1. Introduction

In operational monitoring of a rotating machine, one major goal is to find unexpected or abnormal process state(s)/behavior(s) in machine operations which can be regarded as detection of statistical changes via monitoring numerical variables such as sound emission, cutting force, vibration, temperature, power consumption and so on [2,3]. This technique can overcome a number of real-world engineering problems ranging from early fault detection/diagnosis, safety protection, and many other process monitoring and control problems. Depending on whether requiring a prior learning/training phase, change-point detection algorithms for machine monitoring can be classified into two categories [4]: *supervised* methods (e.g., [5–9]) and *unsupervised* methods (e.g., [3,10,11]). Supervised detection requires a prior learning/training phase to train a change detector using, e.g., SVM [5,6], neural networks [7,8] and fuzzy logic model [9], by taking advantage of collecting a large number of (or at best a full/complete set of) available training samples. Although it tends to have a good balance between response time and accuracy in detection, the further development and commercialization of this method is presently inhibited by a lack of generalization ability of change detectors [4]. Actually it is reasonable because in real applications, the user cannot simulate various engineering scenarios to collect sufficient samples for training a robust and reliable change detector. On the other hand, unsupervised detection is addressed without making any assumption of available training samples. In a standard unsupervised detection architecture, an auto-regressive (AR) model (e.g., Gaussion [3,12] or relatives of Gaussion [10,13], or a simple linear regression model [2]) is used to fit/model the observed data, and then the change point is detected by minimizing the total errors of local model fitting of segments to the data before and after that

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point with a statistical metric, e.g., CUSUM test [3], F_c metric [14] and GLRT test [11]. A larger detection delay is an essential limitation of these methods for real applications [4]. In our study, we propose a new approach where the change is detected only using the data before that change, and thus change decision can be operated by a *real-time* way.

The work in this paper is an extension of our recent article [1]. In [1], we have proposed a generic framework for detecting changes in a monitored machine operational process, where we used the autoregressive-integrated-moving average (ARIMA) model [15] to learn a statistical regularity from the data, then detect the change points by investigating how much each data is deviated from the regularity using *martingale*. In this paper, we extend the previous framework toward two directions:

(a) Considering typical machines have dynamic natures in monitored variables over time [16,17], we take into account such dynamic information for the design of change detection. We take the graph model instead of the ARIMA model for data modeling. By this replacement, the data is represented by graphs with weighted undirected links, and thus a community that is a subgraph whose members are connected strongly to each other is now a key factor to specify characteristics of the data;
(b) We develop a numerical method for computing temporal anomalies in the constructed graphs which indicates how much the monitored data point is deviated from the already observed data. More specifically, a higher anomaly score indicates a higher probability that a change happens, and vice versa.

Besides the methodological extensions of the proposed method, we also present comprehensive experimental results of the method, which outperforms the previous method [1] in various engineering applications.

The rest of this paper is organized as follows. In the Section 2, we describe the proposed framework in details. Section 3 shows experimental results for change detection using the graph-based model. Section 4 gives two possible techniques of using the proposed method for multi-sensor based machine monitoring. At last, we give concluding remarks in Section 5.

2. Graph-based change point detection for machine monitoring

We consider a data stream collected in an operational process of a monitored machine, each of which is specified by measurable variables such as sound emission, cutting force, vibration and power consumption. Two assumptions are first given to support the proposed framework in this paper: (**A**) the measured time-series data is *periodic*, which allows us to divide the collected data stream into a set of sequential cycles according to the estimated periodicity. Thus, by monitoring the amount of fluctuations in these resulted sequential cycles, we can capture the dynamic natures of a machine in its operations; and (**B**) the structural changes are *detectable*, which guarantees the success of change detection from the collected data. For more details, please refer to [1].

In the following, we will present our algorithm to detect structural changes from a monitored data stream. Section 2.1 introduces the graph model and the computation method for construction of it from the data stream. Section 2.2 gives a method of scoring anomalies in the constructed graphs. Section 2.3 shows the detection by using the measured anomalies with martingale-test. Section 2.4 gives the algorithm of the proposed method for practical implementation.

2.1. Model formulation

Given a periodic data stream denoted by $F = \{f_{nT+v}\}, n = 1, 2, 3 \ldots$ where n is the cycle index, T is the period length and v is the phase (timing), obviously this data stream shows a specific and similar structure in each cycle as long as a change does not occur. There have been proposed some data models for capturing such a structure in the data such as using Guassian models and fuzzy logic models mentioned previously. Here, in this paper, we propose to employ the graph model for this purpose.

In general, a graph G consists of a set $\mathscr{V}$ of nodes and a set $\mathscr{E}$ of links, i.e., $G = \{\mathscr{V}, \mathscr{E}\}$, and furthermore, each link has a weight $\omega \in [0, \infty]$ representing the strength of connection. Such a graph can be represented by an adjacency matrix X where each element $x_{i,j}$ indicates the weighted link between the ith node and the jth node (obviously, the adjacency matrix is symmetrical). More specifically, for each cycle of given data, we learn/construct its corresponding graph as follows (see an illustrative example in Fig. 1): the node is the time stamp and the weighted link between two nodes is computed as the Euclidean distance between the measurable values on these nodes. By this modeling, the original stream F is now modeled as a sequence of graphs of cycles, i.e., $F = \{G^1, G^2, \ldots, G^t, \ldots\}$ representing by adjacency matrices $\mathscr{X} = \{X^1, X^2, \ldots, X^t, \ldots\}, X \in \mathbf{R}^{V \times V}, t = 1, 2, \ldots, N$ where G^t is the constructed graph in th cycle and its corresponding adjacency matric is X^t, N is the number of cycles in F, and V is the number of nodes in one graph (i.e., the number of data in each cycle).

A graph may change its communities in the member and/or in the way of connections because of the dynamic nature of machine in its operations. That is, a change happens (**A**) when the densely connected nodes is separated or sparsely connected nodes have dense connections, and (**B**) when the number of nodes increases or decreases. Such community changes can be analyzed by the spectrum of a matrix representing graph [18]. Let us take one adjacency matrix X^t in F for example. We can decompose the symmetrical X^t into $X^t = \Gamma\Lambda\Gamma'$ where Γ is a matrix whose column is an eigenvector of X^t and Λ is a diagonal matrix whose diagonal elements are the real value eigenvalues. The change **A** of *community structure* can be reflected by monitoring Γ, while the change **B** of *community activity* is by Λ [19,20]. As for the problem of change detection